Convergence of Productivity: An Analysis of the Catch-up Hypothesis within a Panel of States

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A consensus appears to have emerged in the literature that per capita income levels and/or levels of productivity in the industrialized market economies have converged significantly over the last century, and especially since the end of the second world war (see, e.g., Abramovitz, Baumol, Baumol and Wolff, De Long, Dollar and Wolff, Dowrick and Nguyen). The results of Abramovitz and Baumol, in particular, highlight these trends. They found an almost perfect inverse relation between labor productivity levels in 1870 and the rate of labor productivity growth between 1870 and 1979 among sixteen OECD countries.

Abramovitz also investigated subperiods and found that labor productivity convergence was much slower in the period before World War II than after. Indeed, even in the postwar period, there is evidence from Abramovitz and from Baumol and Wolff that productivity convergence slowed during the 1970s, though this is disputed by Dowrick and Nguyen, who find parameter stability in their catch-up model between pre- and post-1973 periods when controlling for growth of factor intensities. Results of De Long show little evidence of productivity convergence over the last century when the sample is no longer restricted to OECD countries. However, Baumol and Wolff, using the Summers and Heston's sample, which covers countries at all levels of development, find convergence in real GDP per capita among the top third or so of the countries over the 1950–81 period, though it was weaker than among OECD countries alone. More recently, Dollar and Wolff find evidence of convergence of total factor productivity (TFP) levels both in the aggregate and within industries between 1963 and 1985. However, the disparity in levels of TFP was greater at the industry level, suggesting that countries specialized in different industries. Finally, Ball et al. (2001) find convergence of levels of TFP in agriculture among ten OECD countries between 1973 and 1993.

Various explanations have been proposed to account for the observed tendency for income and productivity levels to converge. Abramovitz and Baumol suggest that technological advances, particularly those embodied in capital equipment, flow from leaders to followers, allowing more rapid growth in economies that start-off technologically backward. In addition to technological catch up, Dowrick and Nguyen hypothesize that convergence may result from differences in the growth rates of factor intensities among countries.

The objective of this article is to determine whether there has been a tendency for TFP levels in agriculture to converge across the United States since 1960, and if so to investigate whether such convergence can be explained by differences in the rates of growth of factor intensities or by productivity catch up.

Data and Methods

The U.S. Department of Agriculture's Economic Research Service (ERS) has recently constructed state production accounts for the farm sector. The salient features of the state accounts are well documented in Ball et al. (1999). Consequently, our focus in this section will be on constructing transitive multilateral comparisons of output, inputs, and TFP.

An index of real output between two states is obtained by dividing the nominal output value ratio for two states by the corresponding

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output price index. We construct multilateral price indexes using a method proposed independently by Eltetö and Köves and Szulc. The "EKS" index is based on the idea that the most appropriate index to use when comparing two states is the binary Fisher index. However, when the number I of states in a comparison is greater than two, the application of the Fisher index number procedure to the $I(I-1)/2$ possible pairs of states gives results that do not satisfy Fisher's circularity test. The problem, therefore, is to obtain results that satisfy transitivity, and that deviate the least from the bilateral Fisher indexes.

Let P_F^{jk} denote the bilateral Fisher price index for state j relative to state k. If P_{EKS}^{jk} denotes the multilateral price index, then the EKS method suggests that P_{EKS}^{jk} should deviate the least from the bilateral price index P_F^{jk}. Thus P_{EKS}^{jk} should minimize the distance criterion:

$$(1) \qquad \sum_{j=1}^{I}\sum_{k=1}^{I}\left(\ln P_{EKS}^{jk} - \ln P_F^{jk}\right)^2.$$

Using the first-order conditions for a minimum, it can be shown that the multilateral price index with the minimum distance is given by (Rao and Banerjee):

$$(2) \qquad P_{EKS}^{jk} = \left(\prod_{i=1}^{I} P_F^{ji}\cdot P_F^{ik}\right)^{1/I}, \qquad j,k = 1,\ldots,I.$$

The EKS price index may therefore be expressed as the geometric mean of the I indirect comparisons of j and k through other states.

Using (2), we construct indexes of relative output prices for all forty-eight states in a single base year. The corresponding output quantity indexes are formed implicitly.[1]

Measures of real input across states require data on relative input prices. Relative prices of capital inputs are obtained based on relative investment goods prices, taking into account the flow of capital services per unit of capital stock in each state (see Ball et al. 2001).

Differences in the relative efficiencies of land across states prevent the direct comparison of observed prices. Our estimates of the relative price of land in each state are based on hedonic regressions. For our cross-section of states, we estimate the following equation by least squares:

$$(3) \qquad \ln\left(P_i^j\right) = \sum_{i=1}^{I}\delta_i D_i + \sum_{c=1}^{C}\beta_c X_{ic}^j + \varepsilon_{ij}, \qquad i = 1,\ldots,I$$

where P_i^j is the price of land in county j in state i, X_i^j is a vector of land characteristics,[2] D_i is a dummy variable equal to unity for the corresponding state and zero otherwise, and ε_{ij} is a stochastic error term.[3] When the log of price is related to linear state dummy variables as in (3), a hedonic price index can be calculated from the antilogs of the δ_i coefficients.[4]

In constructing indexes of relative labor input, we assume that the relative efficiency of an hour worked is the same for a given type of labor in all forty-eight states. Hours worked and average hourly compensation are cross-classified by sex, age, education, and employment class (employee vs. self-employed and unpaid family workers). Since average compensation data are not available for self-employed and unpaid family workers, each self-employed worker is imputed the mean wage of hired workers with the same demographic characteristics. Our indexes of relative labor input are constructed using the demographically cross-classified hours and compensation data.

Fertilizers and pesticides are important intermediate inputs. We construct relative prices

[1] The data are available at the USDA/ERS web site http://www.ers.usda.gov/data/agproductvity/ and can be downloaded as LOTUS or EXCEL spreadsheets.

[2] The land characteristics are derived from climatic and geographic data contained in State Soil Geographic (STATSGO) Data Base (USDA). In addition to environmental attributes, we include "population accessibility" indexes for each county. The indexes are derived from a gravity model of urban development, which provides measures of accessibility to population concentrations (Shi, Phipps, and Colyer). A gravity index accounts for both population size and distance of the parcel from that population. The index increases as population increases and/or distance from the population center decreases. Our construction of the population accessibility index is calculated on the basis of population within a 50-mile radius of each parcel.

[3] The observations on P consist of average prices. When averages are used rather than actual observations, the disturbance term will likely be heteroskedastic. To obtain efficient parameter estimates, we apply weighted least squares, using the land area in each county as weights.

[4] For the semilogarithmic specification used here, Halverson and Palmquist have shown that a consistent estimate of is given by $\exp(\hat{\delta}_i) - 1$.

of fertilizers and pesticides among states from hedonic regression results. A price index for fertilizer is formed by regressing the prices of single nutrient and multigrade fertilizers on the proportion of nutrients contained in the fertilizer materials. Prices for pesticides are regressed on levels of physical characteristics such as toxicity, persistence in the environment, and leaching potential. The quantity indexes for fertilizers and pesticides are formed implicitly by dividing the nominal input cost ratios by the corresponding hedonic price index.

Finally, all our calculations are base-state invariant, but they are not base-year invariant. We use 1996 as the base year for all our time series indexes. The reason for this is that the EKS price indexes are constructed only for 1996, which means that we construct indexes for earlier and later years in the sample by chain linking them to 1996. The result is a "true" panel with both temporal and spatial comparability.

Comparisons of Total Factor Productivity

The data described in the previous section are used to construct indexes of TFP (defined as the ratio of output to an index of capital, labor, and materials inputs) for the forty-eight contiguous states for the 1960–99 period. These indexes, normalized so that the level of TFP for Alabama in 1996 is unity, are available from the UDA/ERS web site (see footnote 1). In table 1 the states are ranked by their level of TFP in 1999. Also included in table 1 is their rank in 1960 and the average annual percentage growth from 1960 to 1999.

One remarkable similarity exists across all states for the full 1960–99 period. Every state exhibits a positive and generally substantial average annual rate of TFP growth. There is considerable variance however. The median TFP growth rate is 1.71% per year. One-third of the states have growth rates averaging more than 2% per year. Two states—Oklahoma and Wyoming—have average annual rates less than 1%. The reported average annual rates of growth range from 0.73% for Oklahoma to 2.59% for Michigan.

The wide disparity of growth rates over the 1960–99 period resulted in substantial changes in the rank order of the states. For example, between 1960 and 1999 Florida rose from third to first, while Georgia rose from thirteenth to second. The largest relative gains in TFP were made by North Carolina and Arkansas. North Carolina improved from sixteenth to fifth among the forty-eight states; Arkansas rose from twenty-fourth to sixth. This relatively rapid TFP growth was, in part, a consequence of the "industrialization" of agriculture, characterized by the expanding presence of large, vertically integrated firms. The industrialization phenomenon has been especially apparent in the Southeastern United States, with accompanying absolute and relative increases in productivity.

Arizona was second among the forty-eight states in 1960, but slipped to seventh in 1999. Oklahoma fell from fourth to thirty-sixth. And Kansas fell from fifth to tenth in terms of relative levels of productivity. West Virginia was last throughout the period. Moreover, its productivity relative to Florida fell from one-half in 1960 to one-third in 1999.

Figure 1 provides details for the intervening years. It plots for each year the coefficient of variation (the ratio of the standard deviation to the mean) of productivity levels for all forty-eight states. We use these coefficients to show that there was some narrowing of the range of levels of productivity over the 1960–99 period, although the pattern of convergence was far from uniform. This is a remarkable result given the wide variation in productivity growth rates. The fact that some states grew more rapidly than others and yet the cross-section dispersion decreased implies that the states that grew most rapidly were those with lower initial levels of productivity, a finding consistent with technological catch up.

Econometric Tests of TFP Convergence

In the previous section, we saw that there has been some narrowing of the range of levels of productivity among states. We now turn to a regression framework to test two hypotheses concerning technology convergence. The first is the catch-up hypothesis, which states simply that those states that lag furthest behind the technology leaders benefit the most from the diffusion of technical knowledge and, hence, should exhibit the most rapid rates of productivity growth. Taking each state as an observation, this hypothesis implies that the rate of growth of TFP is inversely correlated with the level of productivity at the beginning of the period.

Table 1. States Ranked by 1999 Level of Agricultural Productivity

	1999		1960		Average Annual Growth of Productivity 1960–99	
State	Rank	Level	Rank	Level	Rank	Growth
FL	1	1.5938	3	0.7291	12	0.0201
GA	2	1.4611	13	0.6176	7	0.0221
CA	3	1.3795	1	0.7674	35	0.0150
WA	4	1.3536	26	0.5322	3	0.0239
NC	5	1.3333	16	0.5845	10	0.0211
AR	6	1.3103	24	0.5468	6	0.0224
AZ	7	1.2929	2	0.7298	36	0.0147
ID	8	1.2828	19	0.5695	11	0.0208
IA	9	1.2575	8	0.6568	26	0.0167
KS	10	1.1989	5	0.7056	41	0.0136
NE	11	1.1799	11	0.6244	29	0.0163
MS	12	1.1595	37	0.4567	4	0.0239
CO	13	1.1534	6	0.6823	42	0.0135
SD	14	1.1511	9	0.6538	37	0.0145
ND	15	1.1416	22	0.5644	19	0.0181
MN	16	1.1227	18	0.5734	22	0.0172
CT	17	1.1100	41	0.4362	2	0.0240
DE	18	1.0986	21	0.5655	23	0.0170
NY	19	1.0981	14	0.6037	33	0.0153
IL	20	1.0771	17	0.5808	32	0.0158
WI	21	1.0740	15	0.5958	34	0.0151
OR	22	1.0496	42	0.4328	5	0.0227
LA	23	1.0484	39	0.4479	8	0.0218
IN	24	1.0462	30	0.5137	17	0.0182
TX	25	1.0370	12	0.6211	43	0.0131
NV	26	1.0318	10	0.6368	45	0.0124
SC	27	1.0129	31	0.4993	18	0.0181
MD	28	1.0077	27	0.5320	28	0.0164
MA	29	0.9981	43	0.4287	9	0.0217
AL	30	0.9782	29	0.5148	27	0.0165
VT	31	0.9762	20	0.5667	40	0.0139
MO	32	0.9760	23	0.5620	39	0.0142
PA	33	0.9726	35	0.4581	14	0.0193
OH	34	0.9697	40	0.4463	13	0.0199
NM	35	0.9680	28	0.5218	31	0.0158
OK	36	0.9623	4	0.7244	48	0.0073
KY	37	0.9473	36	0.4572	16	0.0187
MI	38	0.9310	47	0.3386	1	0.0259
WY	39	0.9149	7	0.6635	47	0.0082
UT	40	0.9084	33	0.4737	25	0.0167
ME	41	0.9042	38	0.4559	20	0.0176
VA	42	0.8900	34	0.4601	24	0.0169
NJ	43	0.8684	25	0.5405	46	0.0122
RI	44	0.8262	45	0.3893	15	0.0193
MT	45	0.8139	32	0.4954	44	0.0127
NH	46	0.7543	44	0.4019	30	0.0161
TN	47	0.7507	46	0.3804	21	0.0174
WV	48	0.5799	48	0.3317	38	0.0143

The second hypothesis is that technological information is embodied in the factors of production. If the input measures do not correct for input quality, then this hypothesis suggests that the rate of TFP growth will be positively correlated with growth of capital and intermediate inputs. Again, we treat each state as an observation to test this hypothesis.

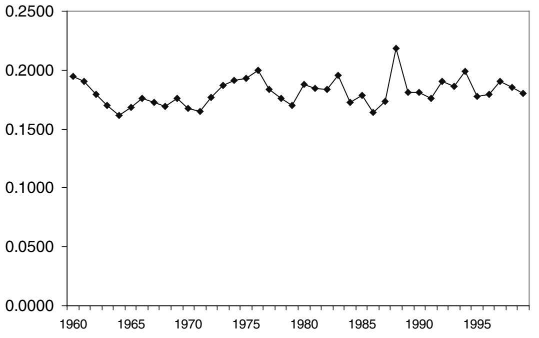

Figure 1. Coefficients of variation of state productivity

Table 2. Panel Data Unit Root Test Statistics

Variable	Levin and Lin's Test Statistics[a]	Im, Pesaran, and Shin's Test Statistics[a]
TFP growth rate[b]	−11.55	−16.14
TFP level[c]	−14.78	−15.13
Capital/labor growth rate[d]	−3.34	−4.33
Material/labor growth rate[d]	−9.40	−13.44

[a] Aysmptotic standard normal, 5% critical value −1.65.
[b] Calculated with a time trend based on preliminary observations. Other variables were calculated without a time trend based on preliminary observations.
[c] Annual observations in natural logarithms.
[d] Calculated without a time trend based on preliminary observations.

To investigate both hypotheses, we employ the basic specification:

$$(4) \qquad \widehat{TFP}_t^i = \beta_0 + \beta_1 \ln TFP_t^i + \beta_2 \left(\frac{\hat{K}}{L}\right)_t^i + \beta_3 \left(\frac{\hat{M}}{L}\right)_t^i + \varepsilon_{it}$$

where *TFP* is the productivity level relative to Alabama at the beginning of each period and $(\frac{K}{L})$ and $(\frac{M}{L})$ are relative factor intensities. The circumflexes (^) denote time derivatives or relative rates of change. Five-year averages are used for the rates of change to reduce random noise. Alabama is excluded from the estimation since the value of the dependent variable is always unity.

In order to minimize the potential for spurious regression results, we first examine whether the behavior of the economic variables in equation (4) is consistent with a unit root. Typically, this analysis has been carried out using tests such as the Augmented Dickey and Fuller's test or semiparametric tests, such as the Phillips and Perron's test. The main problem is that, in a finite sample, any unit root process can be approximated by a trend-stationary process. For example, the simple difference stationary process $y_t = \theta y_{t-1} + \varepsilon_t$ with $\theta = 1$ can be arbitrarily well approximated by a stationary process with θ less than but close to 1. The result is that unit root tests have limited power against the alternative.

Recently, starting from the seminal works of Levin and Lin (2002, 2003), many tests have been proposed for unit roots in panel data. Levin and Lin (2002, 2003) show that by combining the time series information with that from the cross-section, the inference about the existence of unit roots can be made more straightforward and precise, especially when the time series dimension of the data is not very long and similar data may be obtained from a cross-section of units such as countries or industries. A second advantage when using panel unit root tests is that the estimators are normally distributed.

In this article, we employ tests proposed by Im, Pesaran, and Shin and Levin and Lin (2003). These tests are described in detail in Levin, Lin, and Chu. The null hypothesis in both panel unit root tests is that each series in the panel contains a unit root and is, thus, difference stationary. Based on the test statistics reported in table 2, we reject the null hypothesis of a unit root. We proceed by estimating equation (4) assuming stationarity.

The Baltagi and Li's test for serially correlated residuals yields a p-value of 0.0001. This leads us to reject the null hypothesis of no serial correlation.

Next, we estimate a two-way (state and year) fixed effects model with state-specific autocorrelation coefficients and state-specific error variances. An F-test of the joint significance of the state-specific fixed effects yielded a p-value of 0.18. The state-specific fixed effects are then dropped and a one-way (by year) fixed effects model is estimated, again with state-specific autocorrelation coefficients and state-specific error variances. The Akaike Information Criterion (AIC) for the two-way model is −9467 and −9528 for the one-way model. Hence, our final model specification is the one-way fixed effects model with state-specific autocorrelation coefficients and state-specific

Table 3. Regression of Relative Productivity Growth on Relative Productivity Level and Growth in Factor Intensities

	Regressions	
	Without Dummy	With Slope Dummy
ln *TFP*	−0.1631	−0.1635
	(−25.82)***	(−25.80)***
$\left(\frac{\hat{K}}{L}\right)$	0.1230	0.0950
	(5.27)***	(3.71)***
$\left(\frac{\hat{M}}{L}\right)$	−0.0326	−0.3277
	(−1.49)	(−1.48)
$D_{6080} * \left(\frac{\hat{K}}{L}\right)$		0.0656
		(2.76)***
χ^2 value	1136.82	1145.80

***Means significance at the 1% level ($t = 2.576$).

Notes: Regressions use five-year moving averages for rates of change to reduce random noise. All regressions use year fixed effects and correct for autocorrelation and heteroskedasiticity. D_{6080} is a period dummy variable defined as unity on or before 1980 and zero afterwards. The χ^2 value reported is associated with the null model likelihood ratio test. All test statistics are highly significant.

error variances. PROC MIXED in SAS 8.2 is used in estimation.

The results, shown in table 3, confirm the catch-up hypothesis, showing a highly significant inverse relation between the rate of productivity growth by state and its initial level relative to Alabama (column 1). The results for the embodiment hypothesis are mixed. The variable $(\frac{\hat{K}}{L})$ has a positive and significant coefficient (column 1). This result suggests that embodiment of technology in capital was an important source of productivity growth in agriculture.

Net investment in fixed capital was positive for most states through 1980, but was negative thereafter. In a second regression, we include a dummy variable, D_{6080}, defined as unity on or before 1980 and zero thereafter, which interacts with $(\frac{\hat{K}}{L})$ to control for this period effect. The coefficient on the interaction term $D_{6080} * (\frac{\hat{K}}{L})$ is also positive and significant (column 2). We conclude that the embodiment effect was more important during the 1960–80 period when net investment was positive than during the 1981–99 subperiod.

Finally, the coefficient for $(\frac{\hat{M}}{L})$ was negative, but statistically insignificant. We argue that this result reflects our efforts to adjust the input indexes to reflect the improvements in their quality.

Summary and Conclusions

In this article, we estimate the growth and relative levels of agricultural productivity for the forty-eight contiguous states for the period 1960–99. For the full 1960–99 period, every state exhibits a positive and generally substantial average annual rate of TFP growth. There is considerable variance however. The median rate of TFP growth was 1.71% per year, while average growth rates ranged from 0.73% for Oklahoma to 2.59% for Michigan.

The wide disparity in growth rates resulted in substantial changes in the rank order of states. For each year, we compute the coefficient of variation of productivity levels for all forty-eight states. We use these coefficients to show that the range of levels of TFP has narrowed somewhat over time. The fact that some states grew faster than others and yet the cross-section dispersion decreased implies that the states that grew most rapidly were those with lower initial levels of productivity, a finding consistent with technological catch up. Those states that were particularly far behind the technology leaders had the most to gain from the diffusion of technical information and proceeded to grow most rapidly. Finally, we observe a positive and statistically significant relation between productivity growth and growth of the capital-labor ratio, implying embodiment of technology in capital.

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